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RECOGNIZING TWO-DIMENSIONAL OBJECTS

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Abstract

This paper discusses a new model-based approach to recognizing two-dimensional (2-d) objects. In the training phase, each known object is modelled as an ordered sequence of meaningful components of the boundary; each component is, in turn, described by a feature vector. To recognize an unknown object, the unknown object is also represented as an ordered sequence of meaningful components and for each component the corresponding feature vector is obtained. Then a component of a given model is matched against the components of the unknown object representation. If a good match is found, the location and the identity of the unknown object is hypothesized and verified. The proposed approach is capable of recognizing both the fully and the partially visible objects.

1. Introduction

Recently there has been an increasing interest in machine vision systems that are integrated into manufacturing operations (e.g., assembly, inspection, and material handing). Such a machine vision system is called an industrial vision system. An important task in industrial vision is the interpretation of gray-scale images containing two-dimensional (2-d) objects. A number of approaches have been proposed for analyzing such images. Some of these approaches can handle only simple cases where the objects are not allowed to touch or occlude each other, whereas others are capable of handling more general complex cases. Most of the existing 2-d object recognition systems/techniques are model-based. In a model-based system, the predefined or precompiled models (descriptions of the known objects) are used to determine the identity and orientation of the objects present in a given image.

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Model-based matching techniques depend on the type of features used in building the models. Classical statistical pattern classification techniques are usually employed in the cases of global feature-based models [1,2,3,4,5]. The idea is to describe an object by a list of numerical values called a feature vector. These values are usually invariant to translation, rotation, and, possibly, scaling of the object. To recognize an unknown object, its feature vector is computed and usually, a nearest neighbor classification technique is used. However, the global feature-based techniques are incapable of recognizing partially visible objects.

To recognize the partially visible objects, local feature-based techniques [6,7,8,9,10,11,12] are utilized. Most of these techniques employ the object boundary features. In most of these techniques the object boundary or the approximated boundary is described by a set of primitive structural units. This set and the information derivable from it form the basis of both model building and recognition process.

This paper presents a new 2-d object recognition technique that is capable of recognizing partially visible objects. Unlike most of the existing approaches that utilize line segments, corners, or arbitrary segments of the boundary to describe object, we describe an object by an ordered set of its meaningful components.

The organization of the remainder of this paper is as follows. In Section 2, we describe the model/scene description building process. Section 3 discusses the overall recognition process. In Section 4, we present some experimental results. Finally, in Section 5, we offer our conclusions.

2. Model Building Process

In the training phase, the models of the known objects are developed by showing each of the known objects to the system. Figure 1 shows the sequence of operations involved in the overall model building process.

To build the model of a given object, a good contrast image of the object is acquired and it is thresholded to obtain a binary image. The object boundary is traced [13] to obtain an ordered set of boundary points. A polygonal approximation of the object boundary is then obtaind. In our system, curve splitting [15] and the curvature computation method proposed in [14] are

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employed to obtain the vertices of the polygonal approximation of the boundary. Next, the polygonal boundary, so obtained, is decomposed into its meaningful components. A method similar to the one proposed in [16] is used. Figure 2 shows some polygonal approximations and their components. A set of properties are computed for each component. Thus, a component is represented by a feature vector. In the experiments, discussed in Section 4, a component, C, is represented by a feature vector, $< A_c, P_c, L_c, \theta_c, N_c, S_c, T_c, (x_m, y_m), ((x_1, y_1), \ldots, (x_{N_c}, y_{N_c})) >$, where A_c is the area of component C, P_c is the perimeter of component C, L_c and $_c$ are respectively, the magnitude and the orientation of the endpoint vector of component C, N_c is the number of vertices in component C, S_c and T_c are, respectively, the magnitude of the smallest and the largest radial vectors of component C, (x_m, y_m) are the coordinates of the midpoint of the endpoint vector and $(x_1, y_1), \ldots (x_{N_c}, y_{N_c})$ are the coordinates of the N_c vertices of component C. The endpoint vector and the radial vectors of a component are depicted in Figure 3.

3. Component Matching and Object Recognition

In the recognition phase of our system, a representation for the unknown scene is developed using the model building process, discussed in Section 2. To determine the identity and the location of the objects in the unknown scene, a model-driven hypothesize-and-test approach [17] is utilized. The basic idea is to hypothesize the identity and location of an object in the scene by finding a good match for one of its components in the scene. A hypothesis is accepted if a good match is found between the transformed (based on the hypothesized location) model of the hypothesized object and the scene representation, otherwise it is rejected. The overall hypothesis generation and verification process is as follows.

3.1 Hypothesis Generation and Verification

To hypothesize the presence of an object in the scene, the components of that object are compared to the components of the scene. The following properties are used to compare the components: area, perimeter, magnitude of the endpoint vector, number of vertices, magnitude of the largest radial vector, and magnitude of the smallest radial vector. The likelihood that C_0, a component of the object O, matches C_S, a component of the scene, is defined as:

$$\text{Likelihood } [C_0, C_S] = \sum w_p * R^p_{C_0 C_S} \text{ if } |v^p_{C_0} - v^p_{C_S}| < v_{max} \text{ for all properties } p,$$

$$= 1 \text{ otherwise.}$$

Where $\sum$ is taken overall properties p, w_p a weight constant corresponding to property p such that $0 < w_p < 1$ and $w_p =$ $v^p_{C_0}$ and $v^p_{C_S}$ are the values of the propert for C_0 and C_S, respectively. v_{max} is upper bound on the quantity $|v^p_{C_0} - v^p_{C_S}|$ and

$$R^p_{C_0 C_S} = \frac{|v^p_{C_0} v^p_{C_S}|}{v_{max}}$$

Likelihood $[C_0, C_S]$ takes a minimum value zero when for all properties p, $v^p_{C_0} = v^p_{C_S}$ a increases when the discrepency between t values of the properties of C_0 and increases. The maximum value of likeliho $[C_0, C_S]$ is 1 and this is reached if and on if for any property p, $|v^p_{C_0} - v^p_{C_S}| \geq v_{max}$.

A component, C_0, is said to acceptably mat C_S, if the likelihood $(C_0, C_S) < t$, where a threshold. If a component, C_t of the tes model acceptably matches some component, C of the scene, the corresponding object i hypothesized to be present in the scene. T location of the hypothesized object defined in terms of the rotation , t translation in x-direction tx, and th translation in y-direction ty. Thes parameters are computed as follows:

$$\theta = \theta_{C_S} - \theta_{C_t},$$

$$tx = x^s_m - (x^t_m \cos \quad - y^t_m \sin \quad),$$

$$ty = y^s_m - (x^t_m \sin \quad + y^t_m \cos \quad).$$

where (x^t_m, y^t_m) and (x^s_m, y^s_m) are the midpoint of the enpoint vectors of C_0 and C_S respectively.

To verify a given hypothesis, all the point (vertices) of the hypothesized model ar transformed using the hypothesized locatio parameters. If the transformed mode vertices match more than a threshold numbe of scene vertices, the hypothesis is accepte and the corresponding object is declared t be found at the hypothesized location otherwise the given hypothesis is rejected.

4. Experiments

We have tried our technique on several simpl and complex real scenes. In one of thes experiments, models of 3 flat objects wer developed. The polygonal approximations an the components of these objects are shown i Figure 2.

Figure 4 shows a scene consisting of objects occluding each other. The result obtained by our recognition approach ar shown in Table 1. Note that each image i taken to be in the fourth quadrant of standard Cartesian Coordinate System and tha a positive angle of rotation is assumed to b clockwise from the positive x-axis.

5. Conclusion

A new technique for recognizing two-dimension objects is presented. This technique is capable of handling the cases with fully visible objects and the cases with partially visible objects as well. The technique utilizes global features of the meaningful components of the object and scene for generative hypotheses.

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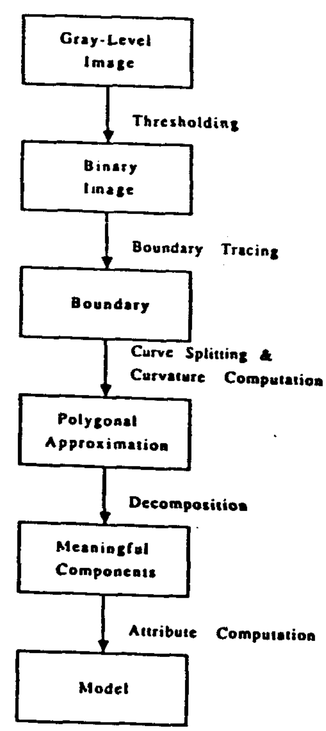
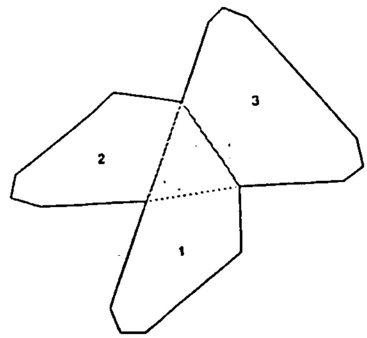
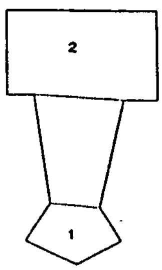


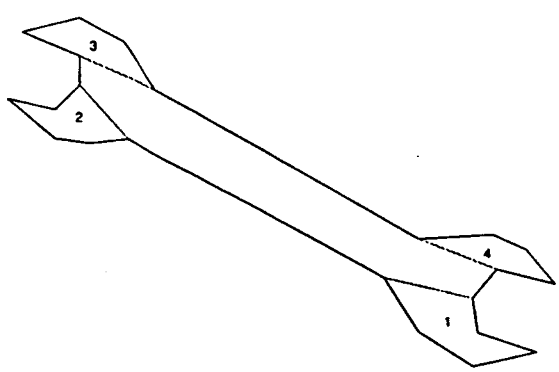
Figure 1. The model building process.



a. Object 1



b. Object 2



c. Object 3

Figure 2. The polygonal approximations and the components of the known objects.

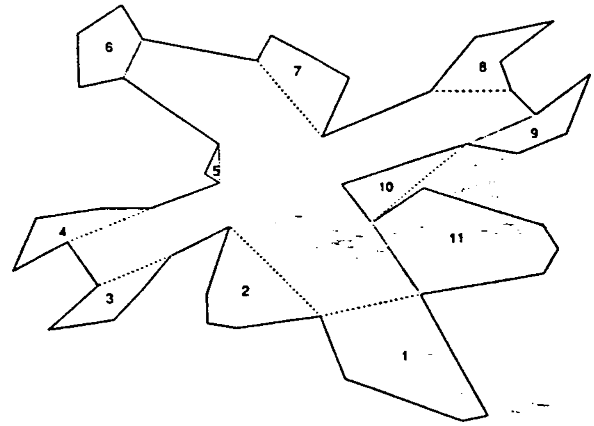


Figure 4. The unknown scene

Table 1: Results for the Scene in Figure 4

Object Id, O	Known Component Id, C_O	Unknown Component Id, C_S	θ	t_x	t_y
1	1	11	114.7	169.7	3
2	1	6	-110.8	-14.1	8
3	3	9	-133.2	105.9	10

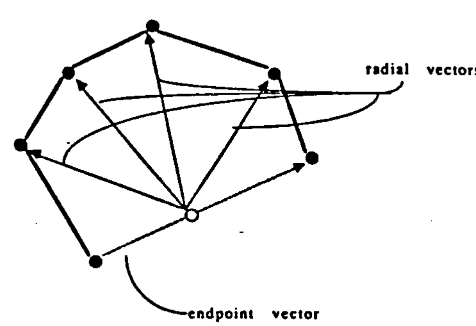


Figure 3. The endpoint vector and the radial vectors of a component.